MJBEM

Malaysian Journal of Business, Economics and Management

journal homepage: https://mjbem.com.my/

Application of Regression Analysis in Forecasting Mobile Broadband Subscriptions Growth for Malaysia

Kar Woh Lon*[1], Mohammed Reyasudin Basir Khan*[1], Chong Peng Lean[2], and Tatchanaamoorti Purnshatman[2]

[1]*Tun Razak Graduate School, Universiti Tun Abdul Razak (UNIRAZAK), Kuala Lumpur, Malaysia.*
[2]*School of Engineering and Computing, MILA University, No 1, MIU Boulevard, Putra Nilai, Nilai 71800, Malaysia.*

KEYWORDS

Mobile Broadband Subscription
5G Network
Growth
Regression Analysis

ARTICLE HISTORY

Received 28 March 2024
Received in revised form 19 April 2024
Accepted 23 April 2024
Available online 27 April 2024

ABSTRACT

This paper forecasts the growth of Mobile Broadband Subscriptions in Malaysia using regression analysis, specifically focusing on linear regression to model trends. The analysis considers factors such as Mobile Broadband Traffic usage and Fixed Broadband Traffic, especially as the 5G network expands and Mobile Broadband becomes a potential alternative for enterprise and education sectors seeking faster broadband solutions. The study also examines Fixed Broadband Traffic in the context of Fixed Mobile Convergence, which impacts Mobile Broadband Subscription growth rates, necessitating the use of multiple linear regression analysis. This work provides a strategic growth plan for Mobile Broadband Subscriptions, highlighting the potential impact of growth trends. Exponential regression is also applied, offering readers a better understanding and the ability to choose results and analyses that best suit their business needs. Trendline reliability is assessed to measure how well the trendline fits the data, enhancing the accuracy of the regression model. For telecommunication companies, this analysis can help identify potential addressable markets and guide network expansion decisions, as well as inform the development of new mobile broadband plans. Original Equipment Manufacturers (OEMs) can use this information to introduce cost-effective mobile broadband devices, while enterprises can strategize their digital transformation efforts based on the findings. The forecast suggests that Mobile Broadband Subscriptions in Malaysia will reach 45.6 million by the second quarter of 2024.

1. INTRODUCTION

Every business applies forecasting to predict future possibly happening situation so that the decision maker can apply the right strategy to increase chances of winning. Forecasting plays a pivotal role in decision-making across various industries, facilitating strategic planning, resource allocation, and risk management. In the education sector, forecasting aids in predicting student enrollment trends, allowing educational institutions to anticipate future staffing needs, setting up adequate smart classrooms, enabling sufficient equipment for laboratories, allocate resources efficiently, and develop long-term strategic plans (Chong, P. L., et al, 2022). In the security industry, forecasting helps identify potential threats and vulnerabilities, enabling organizations to allocate resources effectively, implement preventive measures such as by installation of cybersecurity software and security cameras, and respond to security incidents proactively (Chong, P. L., et al, 2022, Peng Lean Chong, et al, 2023). In energy harvesting, forecasting is essential for predicting energy production from renewable sources and alternative green energy resources, optimizing grid management, and guiding investment decisions in renewable energy infrastructure (Chong, P. L., et al, 2022,

*Corresponding author:
E-mail address: Kar Woh Lon < lon.karwoh@ur.unirazak.edu.my>.
https://doi.org/10.56532/mjbem.v3i1.45

Mohammed Adel Al-badani, et al, 2023, Mohammed Adel Al-badani, et al, 2023).

In manufacturing, forecasting assists in demand planning, production scheduling, and inventory management, ensuring efficient use of resources and timely delivery of products with the help of artificial intelligence, machine learning and internet of things tools to meet customer demand (Peng, C., et al., 2024, Krishna S. R., et al., 2024, Sannasy, K., et al., 2024,Basir, R., et al., 2024). In the IoT sector, forecasting supports capacity planning, network optimization, and resource allocation to accommodate the growing number of connected devices and services ((Ng, P.K. et al., 2023). Similarly, in telecommunications, forecasting guides network capacity planning, service provisioning, and technology investments to meet evolving customer demands and market trends (Wu, L., & K. Sandrasegaran, 2007). In each of these industries, accurate forecasting enables businesses to make informed decisions, mitigate risks, and seize opportunities for growth and innovation.

In the telecommunications industry, forecasting is crucial as it involves the CAPEX investment, OPEX cost, ARPU revenue and many others. Due to Mobile Network Operators having many factors involved and many dependences, this research paper focus on the mobile broadband subscriptions which it will eventually apply into the backend network capacity planning and investment. This paper also applied multiple linear regression analysis to have more independent variables like mobile broadband traffic, mobile broadband penetration rate and fixed broadband traffic to further analysis the growth of mobile broadband subscription.

This paper aims to forecasting mobile broadband subscription growth for Malaysia by applying regression analysis, with linear regression, multiple linear regression, and exponential regression to provide more insight about the Malaysia Broadband subscriptions. Trendline reliability with R-Squared value to provide reader a better understand if the model more reliable. As there is no analysis one size fit all, this research base on more consistent data sources is from KKD [1] and Microsoft Excel to tabulate the result and graph. More comments from analysis apply market insight provide readers insight to make their respective decision.

To have a better analysis, we focus on Mobile Broadband Traffic as another key indicate as it has a very strong relation to the Mobile Broadband Subscription. The consumption of data, have impact or provide strong indication of user behaviour changed and eventually will significantly impact the trend of the Mobile Broadband Subscription. Even though the 5G launch in Malaysia relatively slower compare with neighbouring country like Thailand, Singapore, and Philippines. We cannot deny that Mobile Broadband is “necessity” to a lot of consumers and enterprises and the following analysis is relevant.

2. FORECASTING TECHNIQUES

Regression analysis is a statistical method used to examine the relationship between two or more variables. It helps to understand how changes in one variable and changes in another variable. The analysis involves finding a mathematical equation that best describes the relationship between the variables. Once the equation is found, it can be used to make predictions about one variable based on the values of the other variable(s).

Regression analysis is a powerful tool for analysing data and making predictions or forecasting. Regression Analysis has various types. We are applying Linear regression, multiple linear regression, and Exponential regression in this research. Due to its limitations, I am applying my assumptions into this research paper.

2.1 Simple Linear Regression

Simple linear regression is a statistical method that allows us to study the relationship between two continuous variables, where one variable is considered the independent variable and the other variable is considered the dependent variable. Based on this we can forecast or predict the target with the equation given. The equation for simple linear regression can be expressed as y = mx + b, where y is the dependent variable, x is the independent variable, m is the slope of the line, and b is the y-intercept of the line.

2.2 Multi Regression

Multiple Regression is a statistical analysis technique used to determine the relationship between two or more independent variables (predictors) and a dependent variable. It is often used to predict or explain the outcome of a particular event or phenomenon. The equation for multiple regression is as follows:

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \dots + \beta kXk + \varepsilon \quad (1)$$

where Y is the dependent variable, X1, X2, …, Xk are the independent variables, β0 is the constant or intercept, β1, β2, …, βk are the regression coefficients, and ε is the error term.

2.3 Multi Regression

Exponential Regression is a statistical technique used to model data that exhibits exponential growth or decay. It is often used to predict future trends or to estimate values based on historical data. The equation for exponential regression is as follows:

$$y = ab^{x} \quad (2)$$

where y is the dependent variable, x is the independent variable, a is the starting value of y, b is the growth factor or decay factor, and e is the mathematical constant approximately equal to 2.718.

2.4 Trendline Reliability

Trendline reliability is a statistical tool used to measure the accuracy of a trendline in predicting future values of a variable. It is often used in data analysis to determine how well a trendline fits the data and to assess its reliability. The equation for trendline reliability is as follows:

$$r^{2} = 1 - (SSres \,/\, SStot) \quad (3)$$

where r^2 is the coefficient of determination, SSres is the sum of squares of residuals, and SStot is the total sum of squares. The value of r^2 ranges from 0 to 1, where a value of 1 indicates a perfect fit of the trendline to the data, and a value of 0 indicates no relationship between the trendline and the data. The trendline is more reliable when its r^2 is closer to 1.

2.5 Limitations of Regression Analysis

Regression analysis is a known as powerful forecasting tool, however it cannot apply the external factors in the equation or formula. Those factors namely politic, geographical, population, social and others that cannot be express in number. Comments from the analysis will apply some closely associated factors for consideration although the data is not included.

3. MALAYSIA MOBILE MARKET OVERVIEW

According to our data source from KKD as of Q4 2022, Malaysia having 43.29 million Mobile Broadband Subscriptions with 3.16 Exabytes, 130.99% penetration rate and 3.22 Exabytes for Fixed Broadband. Source from Digital Nasional Berhad reported that Malaysia 5G network Coverage of populated areas (COPA) 54.7%. and expected to achieve 80% by the end of 2024. Post COVID-19, we notice that change of working behaviour, as some organizations practices remote working and e-meeting. This increases the demand for mobile broadband.

3.1 Forecasting on Mobile Broadband Subscription

Mobile Broadband Subscription have been above 130.99% penetration rate, and most likely will continue to growth with riding on 5G wave. In Figure 1, we apply the linear regression with trendline based on y= mx +b. We forecasted Malaysia broadband subscriptions to archive 45,636,060 subscriptions by 2nd quarter of 2024.

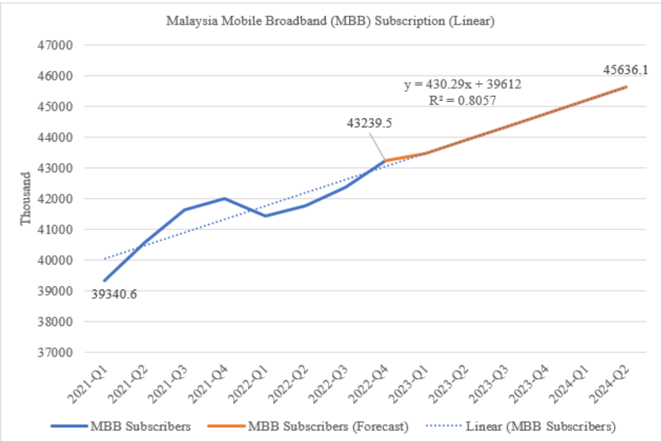


Fig. 1. Malaysia Mobile Brandband (MBB) Subscription Forecast with Linear Trendline.

The trend shows an increase gradually in MBB subscription over time, by applying y = 430.29x +39612 with R2 value is only 80.57%

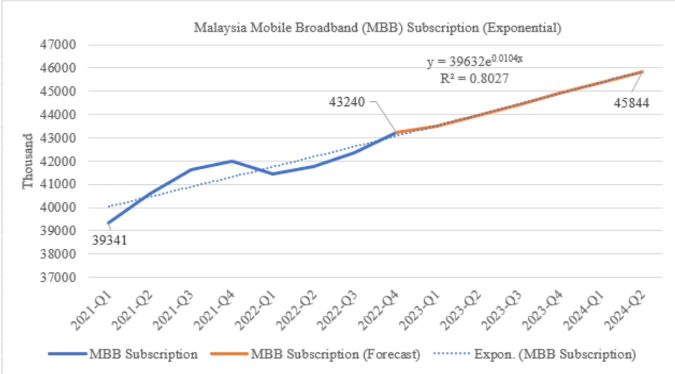


Fig. 2. Malaysia Mobile Brandband (MBB) Subscription Forecast with Exponential Trendline.

Applying the same dataset but using the Exponential regression in Figure 2, y = 39632*EXP (0.0104* forecast Quarter number). We got the 14th quarter or 2nd quarter of 2024 will achieve 45,843,658 subscriptions. With R2 value of 80.27%

Consider both R2 value is only 80% of the variability in the data, so it would be great that we apply more data to forecast the growth of Mobile Broadband subscription.

3.2 Forecasting on Mobile Broadband Traffic

Mobile broadband traffic forecasting analysis can provide various types of information, such as: usage patterns, network performance, security threats, Quality of Service (QoS), revenue generation. With above information can help mobile network operators (MNOs) optimize their network capacity and improve user experience and generate new revenue streams.

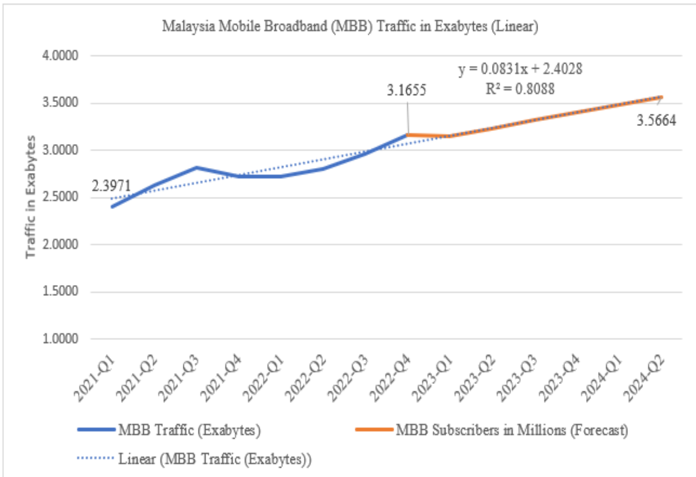


Fig. 3. Malaysia Mobile Brandband (MBB) Traffic Forecast with Linear Trendline.

In Figure 3, we are applying the linear regression and trendline based on y= mx +b. We forecasted Malaysia Broadband traffic to reach 3.5664 Exabytes steadily by 2nd quarter of 2024. With y = 0.0831x + 2.4028 with R2 value 80.88%

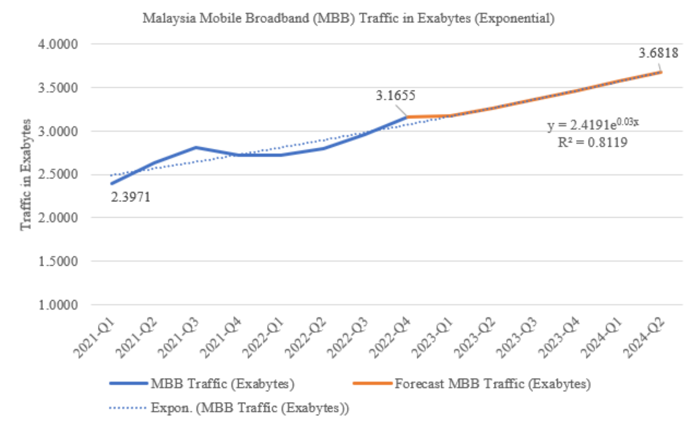


Fig. 4. Malaysia Mobile Brandband (MBB) Traffic Forecast with Exponential Trendline.

In Figure 4, same dataset applied but with the Exponential regression y = 2.4191*EXP (0.03* forecast Quarter number). We got the 14th quarter or 2nd quarter of 2024 will achieve 3.6818 exabytes of Mobile Broadband Traffic increase with R2 value of 81.19% It should slightly higher than linear trendline and the data growth exponentially with 0.1154 exabytes higher.

Due to Mobile Broadband Subscription and Traffic are dynamic and is critical to help the Mobile help mobile network operators (MNOs) to do decision. We use another regression analysis tools to analysis further.

3.3 Multi linear regression analysis

As the Mobile Broadband Subscriptions can be influenced by many factors. Namely (1) Government direction that potentially award the spectrum for Dual Wholesale Network model beside Digital Nasional Berhad. (2) Local Mobile Network Operators trigger merger and acquisition action (3) More affordable 5G terminals or mobile devices that support 5G. (4) Mobile subscription penetration rate higher mean chances of the users adopting the mobility technology faster. (5) Change of use behaviour by using corporate private 5G for their internal network instead of Fixed Broadband. And many others.

Considering the above factors, we apply the collected data set from those in numeric and capable to perform simulation with Multi linear regression analysis. We are using the Mobile Broadband Traffic (exabytes), Mobile Broadband Penetration Rate, and Fixed Broadband (Exabytes) predictors to explore the relationship between the number of Mobile Broadband Subscriptions. Produce the Regression Statistics as show in Table 1 below:

Table 1. Regression Statistics

Regression Statistics	
Multiple R	0.965510735
R Square	0.93221098
Adjusted R Square	0.881369215
Standard Error	404.4260973
Observations	8

From Table 1 we can summarize that the multiple R value of 0.9655 indicates a strong positive correlation between the predictor variables (MBB Traffic, MBB Penetration rate, and FBB Traffic) and the response variable (MBB Subscriptions). The R squared value of 0.9322 indicates that 93.22% of the variability in MBB Subscriptions can be explained by the predictor variables. This suggests that the model is a good fit for the data. The adjusted R squared value of 0.8814 indicates that the model is not overfitting the data, as it accounts for the number of predictor variables used in the model. The standard error value of 404.4261 represents the average distance that the observed MBB Subscription values deviate from the predicted values in the model. Overall, the high R Square and Adjusted R Square values indicate that the model is a good fit for the data, and the low standard error suggests that the model has good predictive power.

Table 2. ANOVA Table

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	8996906.218	2998968.739	18.3355353	0.008419043
Residual	4	654241.8728	163560.4682		
Total	7	9651148.091			

The ANOVA (analysis of variance) table above indicates that the regression model is statistically significant, with an F value of 18.34 and a p-value of 0.0084. This suggests that at least one of the predictor variables is significantly related to MBB Subscriptions.

Table 3. Coefficients Table

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	16375.87537	15670.21019	1.0450323	0.3550001	-27131.603	59883.354	-27131.603	59883.35376
MBB Traffic (Exabytes)	2878.814048	2523.20972	1.1409333	0.3175675	-4126.73923	9884.3673	-4126.73923	9884.367323
MBB Penetration rate	12974.61074	18220.7602	0.7120785	0.5157463	-37614.3297	63563.551	-37614.3297	63563.55122
FBB Traffic (Exabytes)	238.0188058	591.2465172	0.4025712	0.7078501	-1403.54469	1879.5823	-1403.54469	1879.582304

The coefficients table shows the estimates for the intercept and slopes of the predictor variables. The intercept value of 16375.8754 represents the estimated MBB Subscriptions when all predictor variables are equal to zero. The slope values for each predictor variable indicate the change in MBB Subscriptions associated with a one-unit increase in each predictor variable, holding all other predictor variables constant.

The second row of the table represents the coefficient for the predictor variable "MBB Traffic (Exabytes)", which measures the effect of changes in this variable on the dependent variable while holding all other predictors constant. The coefficient for this variable is 2878.814048, which means that an increase of one unit in MBB traffic (in exabytes) is associated with an estimated increase of 2878.814048 units in the dependent variable, while holding all other predictors constant.

The third row of the table represents the coefficient for the predictor variable "MBB Penetration rate", which measures the effect of changes in this variable on the dependent variable while holding all other predictors constant. The coefficient for this variable is 12974.61074, which means that an increase of one unit in MBB penetration rate is associated with an estimated increase of 12974.61074 units in the dependent variable, while holding all other predictors constant.

The fourth row of the table represents the coefficient for the predictor variable "FBB Traffic (Exabytes)", which measures the effect of changes in this variable on the dependent variable while holding all other predictors constant. The coefficient for this variable is 238.0188058, which means that an increase of one unit in FBB traffic (in exabytes) is associated with an estimated increase of 238.0188058 units in the dependent variable, while holding all other predictors constant.

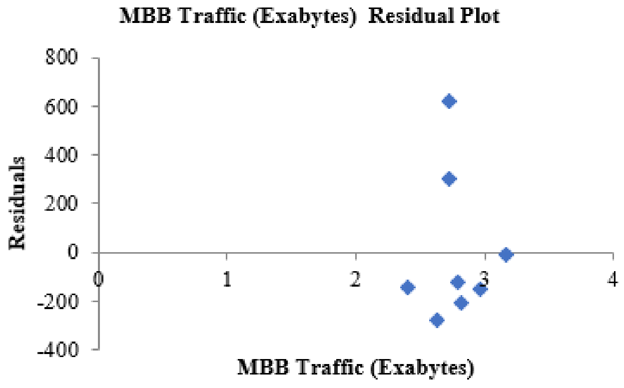
The standard errors for each coefficient estimate provide an estimate of the variability of the coefficient estimate. The t-statistics measure how many standard errors the coefficient estimate is away from zero. The p-values represent the probability of observing a t-statistic as extreme as the one observed, assuming the null hypothesis that the coefficient is zero. The confidence intervals provide an estimate of the range of values within which the true population parameter is likely to lie. The lower and upper 95% confidence interval bounds represent the lower and upper bounds of the interval, respectively, within which the true population parameter is likely to fall with 95% confidence.\

Table 4. Residual Output

Observation	Predicted MBB Subscription in Thousands	Residuals	Standard Residuals
1	39483.07754	-142.4775404	-0.466043292
2	40850.46635	-278.7663529	-0.911843287
3	41836.53837	-206.8383663	-0.676567218
4	41396.80636	619.293642	2.025706274
5	41147.40621	300.4937876	0.982913612
6	41893.98829	-125.3882946	-0.410144458
7	42526.53458	-154.1345841	-0.504173421
8	43251.70829	-12.18229128	-0.039848211

The table shows the residual output for the regression model. The first column indicates the observation number, the second column shows the predicted MBB subscriptions in millions based on the regression model, the third column shows the difference between the predicted and actual values (residuals), and the fourth column shows the standard residuals (residuals divided by the standard error of the estimate). The negative residuals indicate that the predicted value was higher than the actual value, while positive residuals indicate that the predicted value was lower than the actual value. The standard residuals indicate the distance between the observed data and the regression line in units of standard deviation. Overall, the residuals appear to be small in magnitude, indicating that the regression model is a good fit for the data.

Based on the Residual output in table 4, we generate 3 residual plot chat as below: Figure 5 MBB Traffic (Exabytes) Residual Plot, Figure 6 MBB Penetration rate Residual Plot and Figure 7 FBB Traffic (Exabytes) Residual Plot.



Fig, 5. MBB Traffic (Exabytes) Residual Plot

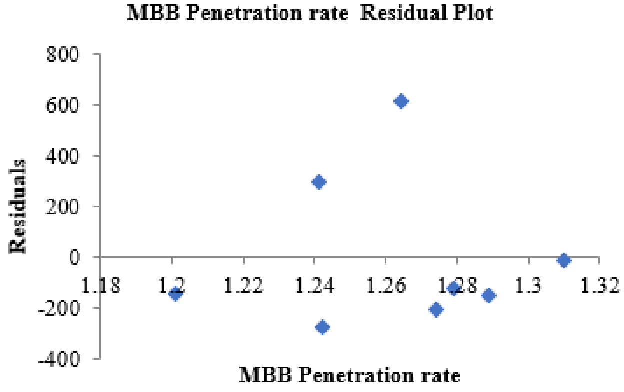


Fig. 6. MBB Penetration rate Residual Plot

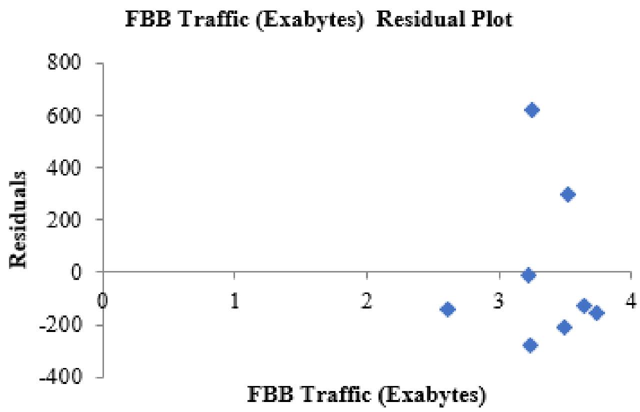
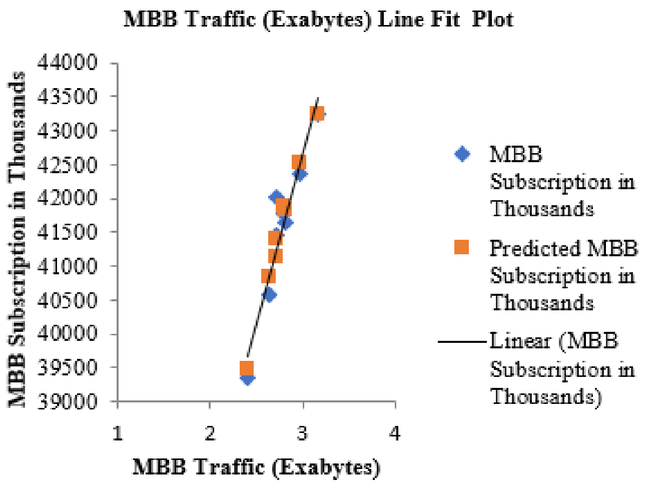


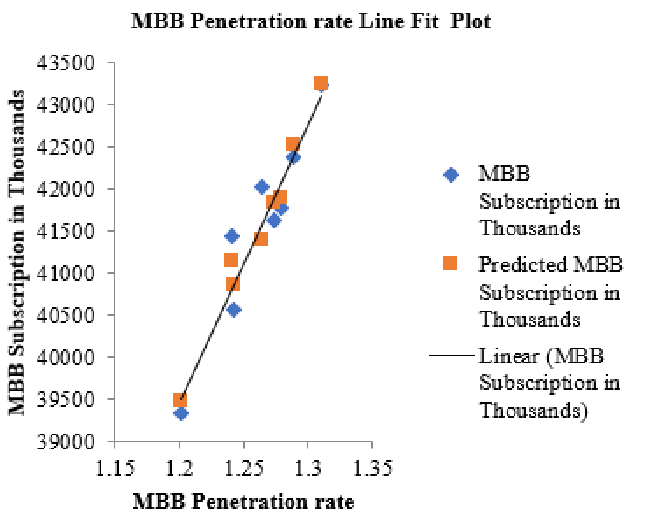
Figure 7. FBB Traffic (Exabytes) Residual Plot**.**

Based on the Residual output in table 4, we generate 3 Line Fit Plot chat as below: Figure 8 MBB Traffic (Exabytes) Line Fit Plot, Figure 9 MBB Penetration rate Line Fit Plot and Figure 10 FBB Traffic (Exabytes) Line Fit Plot.



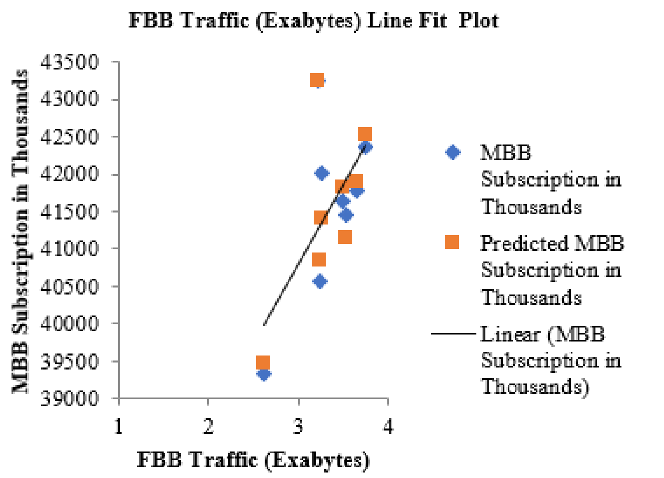
Fig, 8. MBB Traffic (Exabytes) Line Fit Plot.

Figure 8 shows there appears to be a positive linear relationship between Predicted MBB Subscriptions in Thousands and MBB Traffic in Exabytes. The best-fit line slopes upward, indicating that as the number of MBB subscriptions increases, so does the amount of MBB traffic. The slope and intercept of the line can be used to make predictions about MBB traffic given a specific number of subscriptions or vice versa.



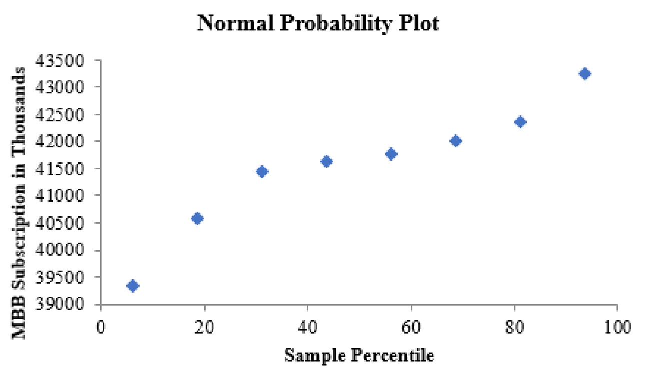
Fig, 9. MBB Penetration rate Line Fit Plot.

As we can see from the Figure 9 plot, there appears to be a positive linear relationship between Predicted MBB Subscriptions in Thousands and MBB Penetration Rate. The best-fit line slopes upward, indicating that as the number of MBB subscriptions increases, the MBB Penetration Rate also increases. The slope and intercept of the line can be used to make predictions about MBB Penetration Rate given a specific number of subscriptions or vice versa.



Fig, 10. FBB Traffic (Exabytes) Line Fit Plot.

As we can see from the plot in Figure 10, there appears to be a positive linear relationship between Predicted MBB Subscriptions in Thousands and FBB Traffic in Exabytes. The best-fit line slopes upward, indicating that as the number of MBB subscriptions increases, the FBB Traffic also increases. The slope and intercept of the line can be used to make predictions about FBB Traffic given a specific number of subscriptions or vice versa.



Fig, 11. Normal Probability Plot

The graph in Figure 11 above shows the MBB subscriptions in millions at various percentiles. For example, at the 6.25th percentile, the estimated number of MBB subscriptions is 39340.6 million. This means that only 6.25% of the sample is expected to have a lower number of MBB subscriptions. Similarly, at the 93.75th percentile, the estimated number of MBB subscriptions is 43239.526 million, meaning that only 6.25% of the sample is expected to have a higher number of MBB subscriptions. The table provides a distribution of MBB subscriptions based on the given data, which can be useful for making predictions or understanding the variability in the data.

4. Conclusion

From the above analysis, we can conclude:

- Mobile Broadband Subscriptions and mobile will continue to growth gradually as shown in the graph Linear. Forecasted to achieve 45,636,000 subscriptions, even though the penetration hit 130.99% penetration rate today.

- Mobile Broadband Traffic will continue to growth exponentially and forecast to achieve 3.6818 Exabytes by 2nd quarter of 2024.
- Mobile Broadband Traffic, Mobile Broadband Penetration Rate, and Fixed Broadband Traffic have strong relevant with the growth of Mobile Broadband Subscriptions. This indicates a strong positive correlation with a multiple R value of 0.9655.

Based on the above conclusion, it is recommended that the Mobile Network Operators should have a better understanding of the growth of Mobile Broadband Subscriptions and have a more addressable market. The network infrastructure should gradually increase and capture the customer with a more attractive plan. This can be seen from the Mobile Broadband Traffic increasing exponentially.

The more dataset collected, and the survey is needed to have a better understanding and analysis to provide more insight. Those information likes Average Revenue Per Subscriptions (ARPU), Traffic Type (Gaming, social media, Video, meeting, productivity tools and many others.), spending time, geographical demand and coverage, annual income per subscriptions, mobile broadband devices available in the market and many others. The more details we collect the more accurate and targeted analysis can be performed and proposed. The result will also be accurate.

Regression analysis is a great tool for forecast and analysis. If we can apply more techniques and apply decision tree to analysis the macro and micro economy, PESTLE analysis (Political, Economic, Sociological, Technological, Legal and Environmental). This will enable the decision maker to have more information to make the right decision.

REFERENCES

Almeida, D., Pasupuleti, J., Raveendran, S. K., & Basir Khan, M. R. (2021). Performance evaluation of solar PV inverter controls for overvoltage mitigation in MV distribution networks. Electronics, 10(12), 1456. https://doi.org/10.3390/electronics10121456

Basir, R., Jabbar Al-Fattah, Gazi, Ahmad Anwar Zainuddin, Chong Peng Lean, Saidatul Izyanie Kamarudin, & Miqdad Abdul Aziz. (2024). Accelerating Electric Vehicle Adoption on Malaysian Islands: Lessons from Japan's Islands of the Future Initiative. Lecture Notes in Electrical Engineering, 109–115. https://doi.org/10.1007/978-981-99-9005-4_14

Chen, J. (2019). Line Of Best Fit. Investopedia, https://www.investopedia. com/terms/l/ line-of-best-fit.asp

Chong, P. L., Ganesan, S., Ng, P. K., & Kong, F. Y. (2022). A TRIZ-Adopted Development of a Compact Experimental Board for the Teaching and Learning of Operational Amplifier with Multiple Circuit Configurations. Sustainability, 14(21), 14115. https://doi.org/10.3390/su142114115

Chong, P. L., Than, Y. Y., Ganesan, S., & Ravi, P. (2022). An Overview of IoT Based Smart Home Surveillance and Control System: Challenges and Prospects. Malaysian Journal of Science and Advanced Technology, 54–66. https://doi.org/10.56532/mjsat.v2iS1.121

Chong, P. L., Singh, A. K., & Kyong, F. Y. (2022). Renewable Energy from Living Plants to Power IoT Sensor for Remote Sensing. ADBU Journal of Engineering Technology, 11(1).

Digital Nasional Berhad on Target for 80% 5G Nationwide Coverage in 2024; end 2022 target exceeded, reaching ~50%. (n.d.). Digital Nasional Berhad. https://www.digital-nasional.com.my/digital-nasional-berhad-target-80-5g-nationwide-coverage-2024-end-2022-target-exceeded-reaching-50

Facts and Figures - Interactive Dashboard | Malaysian Communications And Multimedia Commission (MCMC). (n.d.). Malaysian Communications and Multimedia Commission (MCMC) | Suruhanjaya Komunikasi Dan Multimedia Malaysia (SKMM). Retrieved March 26, 2024, from https://www.mcmc.gov.my/en/resources/statistics/facts-and-figuresinteractive-dashboard

Khan, M. R. B., Jidin, R., & Pasupuleti, J. (2016). Energy audit data for a resort island in the South China Sea. Data in brief, 6, 489-491. https://doi.org/10.1016/j.dib.2015.12.033

Khan, M. R. B., Jidin, R., & Pasupuleti, J. (2016). Data from renewable energy assessments for resort islands in the South China Sea. Data in brief, 6, 117-120. https://doi.org/10.1016/j.dib.2015.11.043

Krishna Sannasy Rao, Peng, C., Poh Kiat Ng, Feng Yuan Kong, Reyasudin, M., Ismail, D., & None Chen Li. (2024). AI and ML in IR4.0: A Short Review of Applications and Challenges. Malaysian Journal of Science and Advanced Technology (Online), 141–148. https://doi.org/10.56532 /mjsat.v4i2.291

Malaysia's telcos call for dual wholesale network, but decline to share details. (n.d.). The Edge Malaysia. Retrieved March 26, 2024, from https://www.theedgemarkets.com/article/malaysia-telcos-call-dual-wholesale-network-decline-share-details

Mohammed Adel Al-badani, Peng Lean Chong, & Heng Siong Lim. (2023). Enhancing microbial fuel cell performance with carbon powder electrode modifications for low-power sensors modules. International Journal of Renewable Energy Development, 13(1), 80–87. https://doi.org/10.14710 /ijred.2024.58977

Mohammed Adel Al-badani, Peng Lean Chong, & Heng Siong Lim. (2023). A mini review of the effect of modified carbon paper, carbon felt, and carbon cloth electrodes on the performance of microbial fuel cell. International Journal of Green Energy, 21(1), 170–186. https://doi.org/10.1080/15435075.2023.2194979

Montgomery, D. C., Peck, E. A., & G Geoffrey Vining. (2013). Introduction to linear regression analysis. Solutions manual. Wiley-Blackwell.

Ng, P. K., Chong, P. L., Yeow, J. A., Ng, Y. J., & Nathan, R. J. (2023). Ergonomic Work from Home Recommendations Using TRIZ:"Stop Robbing Peter to Pay Paul". In Human Factors in Engineering (pp. 67-83). CRC Press.

Peng Lean Chong, Ismail, D., Poh Kiat Ng, Feng Yuan Kong, Reyasudin, M., & Sargunam Thirugnanam. (2024). A TRIZ Approach for Designing a Smart Lighting and Control System for Classrooms Based on Counter Application with Dual PIR Sensors. Sensors, 24(4), 1177–1177. https://doi.org/10.3390/s24041177

Peng Lean Chong, Ganesan, S., Yin Ying Than, & Ravi, P. (2023). Designing an Autonomous Triggering Control System via Motion Detection for IoT Based Smart Home Surveillance CCTV Camera. Malaysian Journal of Science and Advanced Technology, 80–88. https://doi.org/10.56532 /mjsat.v2is1.120

Sannasy, K., Peng, C., Kong, N., Ng, N., None Chen Li, Reyasudin, M., & Ismail, D. (2024). Transformative Applications of IoT in Diverse Industries: A Mini Review. Malaysian Journal of Science and Advanced Technology (Online), 130–140. https://doi.org/10.56532/mjsat.v4i2.292

Seet, C. C., Pasupuleti, J., & Khan, M. R. B. (2019). Optimal placement and sizing of distributed generation in distribution system using analytical method. International Journal of Recent Technology and Engineering, 8(4), 6357-6363. https://doi.org/10.35940/ijrte.D5120.118419

Welcome to STAT 462! | STAT 462. (n.d.). Online.stat.psu.edu. https://online.stat.psu.edu/stat462/

Wu, L., & K. Sandrasegaran. (2007). Forecasting Asia Pacific Mobile Market Trends Using Regression Analysis. OPUS - Open Publications of UTS Scholars (University of Technology Sydney). https://doi.org/10.1109/icmb. 2007.30

Zahraoui, Y., Alhamrouni, I., Basir Khan, M. R., Mekhilef, S., P. Hayes, B., Rawa, M., & Ahmed, M. (2021). Self-healing strategy to enhance microgrid resilience during faults occurrence. International Transactions on Electrical Energy Systems, 31(12), e13232. https://doi.org/10.1002/2050-7038.13232